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Resource Allocation for Cell-free Networks with Reflective Intelligent Surfaces

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Grazie a tutti che mi hanno aiutato da vicino o lontano.

"Imagination Is More Important Than Knowledge"

A.Einstein

List of Acronyms

MPC model predictive control

TLA Three Letter Acronym

BS Base Station

IRS Intelligent Reflecting Surface

UE User Equipment

CS Channel State

CSI Channel State Information

5G Fifth Generation

6G Sixth Generation

MIMO Multiple Input Multiple Output

3GPP Third generation Partnership Project

mMIMO Massive Multiple Input Multiple Output

mmWave Millimeter Wave

TDD Time Division Duplex

FDD Frequency Division Duplex

SE Spectral Efficiency

MU-MIMO Multiple User Multiple Input Multiple Output

LTE Long Time Evolution

LSAS Large Scale Antenna Systems

SISO Single Input Single Output

ZF Zero Forcing

OFDM Orthogonal Frequency Division Multiplexing

LoS Line Of Sight

NLoS Non Line Of Sight

SNR Signal to Noise Ratio

CA Co-Located Antenna

DA Distributed Antenna

CSIT Channel State Information at Transmitter

BD Block Diagonalization

DWCS Distributed Wireless Communication Systems

VBS Virtual Base Station

MT Mobile Terminal

CDMA Code Division Multiple Access

SUMF Single User Matched Filter

MMSE Minimum Mean Square Error

OFDMA Orthogonal frequency Division Multiple-Access

MCP Multiple Cluster Points

DAS Distributed Antenna Systems

ICI Inter Cell Interference

WINNER Wireless World Initiative Radio

MS Mobile Station

SINR CSignal to Interference Noise Ratio

CoMP Coordinated Multi Points

AP Access Point

eNB Evovlved Node B

SDMA Space Division Multiple Acces

MU-CoMP Multi User Coordinated Points

PRB Physical Resource Block

TTI Transmit Time Interval

CPU Central Processing Unit

C-RAN Cloud Radio Access Network

ADC Analog to Digital Converter

WIFI Wireless Fidelity

IEEE Institute of Electrical and Electronics Engineers

ULA Uniform Linear Arrays

CB Conjugate Beamforming

NR New Radio

AF Array Factor

CSCG Complex Circular Symmetric Gaussian

PDF Probability Density Function

SVD Singular Value Decomposition

Contents

List of Figures

Abstract

The explosive demand for higher data rates and traffic volume, wireless communication networks are required to provide better coverage, and uniform user performance over a wide coverage area which 5G cannot satisfy. One of the issues to be addressed, is the inter-cell interference significantly degrades the cell-edge performance. In this work, we will introduce relevant techniques that will be implemented in the sixth generation of wireless communication (6G). Additionally, we will present relevant results about the performance of a proposed system in downlink, by deploying resource allocation for cell-free massive multiple-input-multiple-output (mMIMO) wireless communication networks using Intelligent Reflective Surfaces (IRS).

Introduction

The demand for higher data rates and traffic volumes seems to be never-ending, thus the quest for delivering the required services must also continue. The cellular network technology has evolved from using fixed sector antennas to flexible multiple antenna solutions. Recently, the first release of 5G New Radio (NR) was finished by the 3rd Generation Partnership Project (3GPP) and the first commercial networks are already operational. In particular, massive multiple-input multiple-output (MIMO), is a key technology where base stations having a number of antennas at least, an order of magnitude more than the number of user equipments (UEs). However, this is not the end of the MIMO development. As access to wireless connectivity becomes critical in our everyday lives, our expectations of ubiquitous coverage and service quality continue to grow. Many future requirements can be conceived, which cannot be addressed by 5G; for example, exceptionally high bit rates, uniform user performance over the coverage area, ultra-low latencies, high energy efficiency, robustness against blocking and jamming, and wireless charging. There is no simple way to meet these requirements. There has been significant focus on using millimeter wave (mmWave) frequencies in 5G, since large unused bandwidths are available in these frequency band, which might translate into higher bit rates. Unfortunately, there are some fundamental drawbacks with mmWave communications. First, the sensitivity to signal blockage is challenging, despite significant research efforts that have been devoted to the issue in the past decade. Second, the shorter wavelength in mmWave bands leads to a reduced coherence time, thus one has to multiplex fewer data signals than in sub-6 GHz bands to achieve the same signaling overhead for channel state information (CSI) acquisition. These problems presumably become worse in the sub-terahertz (THz) bands, above 0.1 THz, that are currently being studied for beyond 5G. The bottom line is that there is a need to develop novel multiple antenna technologies that can be applied in the valuable sub-6 GHz spectrum as well as in higher bands, and to consider both time-division duplex (TDD) and frequency-division duplex (FDD) modes. It is time to analyze what lies beyond 5G, or rather what the current multiple antenna technologies can potentially evolved into, beyond what is currently envisaged. Potential paradigm shifts in wireless network design for beyond 5G are cell-free massive MIMO, beamspace massive MIMO, and intelligent reflecting surfaces (IRSs). These topics are covered in the end of the next chapter.

The rest of the thesis is organized as follows. In Chapter 1, the literature on related topics is covered, where 5G drawbacks and limitations were stated together with introduction of novel techniques that will be used in 6G. In Chapter 2, the problem formulation and some solutions are proposed. In Chapter 3, we present numerical results and discussion. Finally in Chapter 4, an overview of the results and some concluding remarks are presented.

Chapter 1

Litterature Review

1.1 Introduction to MIMO

Since 2019, the fifth generation (5G) of wireless communication networks has been deployed worldwide to achieve massive connectivity, ultra-reliability and low latency. Among the significant enabling technologies in 5G we find multiple-input multiple-output (MIMO) and massive multiple-input multiple-output (mMIMO).

The authors in [1] noticed that with massive MIMO we can achieve noticeable improvements in terms of spectral and energy efficiency by using relatively simple linear processing, and exploiting a large number of antennas at the base station (BS) in a centralized manner, which can provide very high beamforming and spatially multiplexing gain. Before massive MIMO, scientists had to consider first a point-to-point MIMO link, where each end-point device was equipped with multiple antennas to communicate with other devices.

Afterwards, an enhanced scenario was considered, where the base station (BS) was equipped with multiple antennas simultaneously serving a set of single-antenna users, resulting in a multi-user MIMO (MU-MIMO). With such system, results have shown an increase of system capacity, since the number of users is increased.

Also, due to multi-user diversity, the performance of MU-MIMO systems is generally less affected by propagation phenomenon than point-to-point MIMO links. With such enhancements and mentioning the fact that the base station can be much expensive than the user equipments, since this latter can contain cheap single-antenna devices, MU-MIMO has become an integral part of communications standards such as 802.11 (Wi-Fi), 802.16 (WiMAX) and LTE. Unlike MIMO, where base stations can have up to 10 antennas with a slight increase in spectral efficiency, authors in [1] have also introduced large-scale antenna systems (LSAS) also known as massive MIMO, where BS is equipped with a number of antennas that can start from 100, improving by this the spectral efficiency of 40 users in a 20MHz channel in both uplink and downlink to 26.5 bit/s/Hz and reaching a data rate of 17 Mb/s with an average throughput of 730 Mb/s per cell.

Moreover, it turned out in [3] that the effects of uncorrelated noise and small-scale fading are eliminated due to fact the BS has a significant larger number of antennas than the number of users within the cell, a large number of degrees of freedom are introduced and it will be useful to decrease or null interference. Indeed, in practical scenarios massive MIMO systems need to keep the complexity of used algorithms the minimum. From energy efficiency perspective, massive MIMO is one of the important schemes that can be adopted, since it can significantly extend the range of operation compared with a single antenna system if an adequate transmit power is available. Furthermore,comparing with a single antenna system, massive MIMO can scale down its transmit power proportional to the number of antennas at the BS with perfect channel state information (CSI) or the square root of the number of BS antennas with imperfect CSI, yielding the same performance as a single-input single-output (SISO) system as described in [4].

In [5], more details about massive MIMO were discussed including issues on channel estimation and signal detection, transmit precoding schemes, the MF precoder/detector, other linear schemes such as minimum mean-squared error (MMSE) and zero-forcing (ZF) precoders/detectors are discussed based on either single-cell processing or multi-cell coordinated processing. Additionally, the so-called pilot contamination effect, caused by employing non-orthogonal pilot sequences at different users in different cells, is discussed in detail. The energy efficiency of massive MIMO systems is also analyzed. However, instead of using orthogonal frequency division multiplexing (OFDM) as in most MU-MIMO implementations, the possibility of single-carrier modulation for massive MIMO systems is also discussed. Finally, the challenges and potentials related to applications of massive MIMO in future wireless communications are identified later in this paper.

Authors in [6] were discussing the high capability of large-scale antenna systems (LSAS) or massive MIMO by using beamforming and frequency response flattering techniques to provide uniform multi Mbps throughputs to all intra-cell users. Comparing with the legacy LTE systems, a 64-antnna LSAS can provide cell edge throughputs with at least ten-fold increase in uplink and downlink, while old fashioned macro-cellular wireless networks are not even capable to feed all the users inside the cell, due to large variations in slow fading inter-cell and inter-user interferences, which implies that the edge users are totally sacrificed to achieve an acceptable level of cell spectral efficiency. Hence, LSAS are proven to be capable to achieve huge spectral efficiency by devising simple power controls that provide uniformly multi-megabits-per-second throughputs, in both uplink and downlink to all users in a macro cellular LSAS coverage area, and this is in fact due to its many service antennas that are able to concentrate the power to the mobile terminals regardless how much they are spread in the cell, which is not the case for LTE systems where the power control is not that efficient. Additionally, the power control is frequency independent since the frequency response of the channel can be filtered out by many service antennas, which means that all frequencies are typically convenient from power control perspective.

Unlike legacy LTE systems, where power controls in both uplink and downlink are obtained by solving systems of linear equations that give relevant results for scenarios where each cell serves a similar number of users (static or fixed wireless networks), but not for cases where we have random numbers of users in with different cell sizes (mobile networks), because for this latter the power controls will force a lower user throughput for cells with less number of users than a crowded cell with much users, which is unfair for cells with few users. Therefore, a solution was provided in [6] by exploiting LSAS or massive MIMO to provide power controls for a macro cellular network, which can deliver uniform and maximal equalized user throughput regardless its position inside each cell.

1.2 Favorable propagation and channel hardening

Additionally, one of the reasons why low latency and high reliability are assured in 5G systems using MIMO technology is the channel hardening phenomenon. By increasing the number of antennas at the base station and exploiting the spatial diversity, the channel gain variations in terms in time and frequency domain decrease [8]. With channel hardening, the channel starts to behave almost deterministically and the effect of fast-fading decreases, which means that the issue with small scale fading decreases and leaves only the large-scale fading to handle. This makes channel estimation and power allocation easier among other phenomena. Actually, we can divide channel hardening effects into two main categories, the first one is when the delay spread is decreased, which means that fading over frequency become more lower or even negligible. The second one, is when coherent interference between signals coming from many base stations occurs, the fading in time decreases.

Overall authors have presented a measurement-based evaluation of channel hardening in a practical scenario, where channels are measured with 128-port cylindrical array for nine single antenna users in an indoor environment. In such a scenario, between 3.2 to 4.6 dB have been a reduction of the standard deviation of the channel gain that can be expected depending on the amount of user interaction. The measurements were also done in line of sight scenario (LoS) and no line of sight (NLoS) scenarios, and in both cases standard deviation of channel gain was decreased by increasing the number of antennas at the base stations.

1.3 Massive MIMO in distributed or collocated setup

Massive antenna arrays at the base station can be deployed in collocated or distributed setups. When service antennas are located in a compact area, we are then talking about collocated massive MIMO architectures, thus benefiting from advantages of low backhaul requirements. In contrast, when service antennas are spread over a large area, we are directly referring to distributed massive MIMO systems, offering by this much higher probability of covering all users within a cell by exploiting in an efficient way the diversity against the shadow fading, while sacrificing by this the low cost of backhaul requirements.

Authors in [7] presented a comparative study on the downlink rate performance of MIMO cellular networks with co-located and distributed BS antennas and explore how the rate scaling behavior varies with different BS antenna layouts when a large number of BS antennas are employed. In fact, for a point-to-point system with M transmit and N receive antennas, the capacity grows linearly with $min(M, N)$ in a rich-scattering environment. With a large number of collocated antennas at both the BS and the user sides, nevertheless, the capacity may be severely reduced due to strong antenna correlation.

If the BS antennas are grouped into geographically distributed clusters

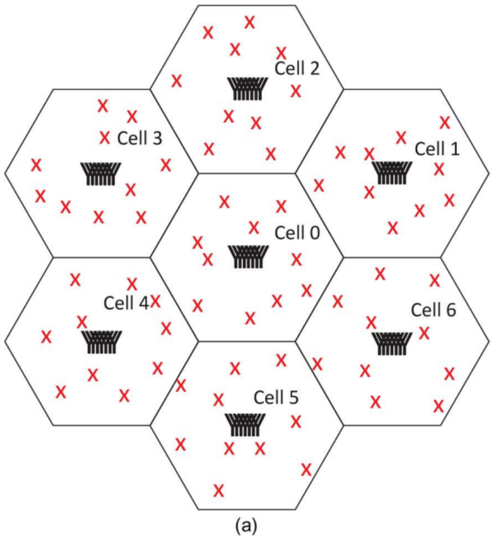

Figure 1.1: A hexagonal cellular network with K uniformly distributed users in each cell and M BS antennas with two antennas with two antenna layouts : (a) with the CA layout, and (b) with DA layout "Y" represents a BS antenna and "X" represents a user.

and connected to a central processor by fiber or coaxial cable, signals from distributed BS antennas to each user are subject to independent and different levels of large-scale fading. In the meanwhile, the implementation cost of distributed BS antennas also becomes significantly higher than that of the co-located ones, especially when the number of distributed BS antenna clusters is large. It is therefore, of great practical importance to compare the rate performance of cellular networks under different BS antenna layouts to see if the increased cost is justified for both scenarios, single user and multiple-users cases. 1.1 illustrates both distributions DA and CA.

In the single-user case, the ergodic capacity of a point-to point MIMO channel has been extensively studied in the last few years. With co-located antennas at both sides, the ergodic capacity can be fully described as a function of the average received signal-to-noise ratio (SNR) since all the transmitted signals experience the same large-scale fading, also when the number of antennas is large, asymptotic results from random matrix theory were also successfully applied to characterize the ergodic capacity. By assuming that the number of antennas on both sides grow infinitely with a fixed ratio, the asymptotic ergodic capacity of a point-to-point MIMO channel was shown to be solely determined by the average received SNR and the ratio of the number of transmit antennas to the number of receive antennas.

On the other hand, the ergodic capacity for distributed BS antennas depends on the positions of the user and BS antennas. Assuming that BS antennas are grouped into L geographically distributed antenna clusters and taking into consideration that the number of antennas for both BS and users grow to infinity with a fixed ratio, the asymptotic ergodic capacity of a distributed MIMO channel is given as an implicit function of L large-scale fading coefficients [10].However, when the number of BS antenna clusters L becomes larger , the average ergodic capacity will be increasingly more difficult to obtain due to high computational complexity. Fortunately, authors in [7] derives that asymptotic bound would be helpful to characterize the scaling behavior of the average ergodic capacity in distributed MIMO channels.

In fact, in order to provide a general scenario and give a reasonable performance lower-bound, authors didnât consider a regular BS antenna layout, but instead they consider a random layout, since it will be more challenging to place BSs in a regular manner due to geographical conditions. As a result, two layouts were considered, a co-located antenna (CA) layout and a distributed antenna (DA) layout, where both are exploiting downlink single-user system with M BS antennas and N co-located antennas at the user. In the CA layout, the BS antennas are co-located at the center of the cell, while in the DA layout, BS antennas are grouped into M/N clusters which are uniformly distributed within the inscribed circle of the hexagonal cell.

Furthermore, channel state information (CSI) can noticeably affect capacity gains, hence it is of great importance to study the capacity with CSI at the transmitter side (CSIT) of the distributed MIMO channel, especially when the transmit antenna are much larger than the received one, i.e. $M >> N$ where substantial capacity gains can be achieved by optimally allocating the transmit power according to CSI. Authors in [7], were assuming that perfect CSI is available at both the BS and the user sides, and they provided an asymptotic analysis of the per-antenna capacity with $M, N \to \infty$ and $M/N \to$ L»1 .

More than that, they have stated that the asymptotic per-antenna capacity with the CA layout and an asymptotic per-antenna lower-bound capacity with the DA layout are derived, are both dependent on the minimum access distance of the user. Moreover, the analysis shows that the asymptotic average per-antenna capacity with the CA layout and the asymptotic lower-bound of the average per-antenna capacity with the DA layout both logarithmically increase with L, but in the orders of $\log_2 L$ and $\frac{\alpha}{2} \log_2 L$, respectively, where $\alpha > 2$ denotes the path-loss factor. In fact, when the number of cluster L is large, and by reducing the minimum access distance a much higher capacity is achieved in the DA case.

Now, considering the case where a multi-user cellular system is implemented, the downlink rate performance of each user is crucially determined by the precoding strategy. An orthogonal linear scheme called block diagonalization (BD) was considered by authors since it is more used and provide lower complexity and near-capacity performance when the number of BS antennas is large [11]. The BD scheme is projecting the user's signal to the null space of all other users channel gain matrices, eliminating by this the intra-cell interference.

Even though DA layout has shown a better average rate performance, the inter-cell interference was observed to be sensitive to the user's position at the cell edge, leading to a large rate difference among cell-edge users. To achieve a uniform rate across the cell, proper transmit power allocation should be performed at each BS so that we will insure a constant SINR for all the users, especially in the case of a large number of BS.

1.4 Distributed MIMO

In [9] distributed wireless communication systems or (DWCS) are considered, where every layer is distributed, and the most important concept is the distributed processing of wireless signals that is performed according to a parallel paradigm, where the processors are separated from antennas. Each processor belongs to the processing layer that can be considered as central processing unit, which controls signals that are transmitted/received form many antennas distributed in the area, by considering the nearest co-processors so that the capability of the channel can be fully utilized by a mechanism similar to MIMO. In case of failure of one of the processors, the tasks can be assigned to another one, since the processing structure is inherited from software radio, or network radio, which is based on configurable on high-speed connectivity among processors making by that interworking and processing tasks dynamically arranged and delivered between them, which results an increase of the reliability of the system. This technique came as a solution of the traditional cellular systems whose signal processing is manipulated at the BS for each cell, causing by that more latency and degradation is systemâs performance.

According to the previous description, we can state that in DWCS, the processing function for a user of a certain region is no longer belonging to a certain BS or certain processor, but instead depends on the position of the user while it is moving, creating by that a new concept called virtual base station (VBS). A VBS in fact, performs signal processing for users within its range and not necessarily for a specific identified user.

In the case of overlapping area, data communication among VBSs is crucial so that signal processing will be performed through the signal processing unit. The concept of VBS, will bring together another one, which is called virtual cell. While the traditional cell is base-station-centered, a virtual cell is instead a set of distributed antennas, where a user can have its own virtual cell, creating what we call a mobile-terminal-centered or MT-centered virtual cell.

This concept will be useful in terms of total system's capacity, where MIMO techniques can be evolved to cancel out or dramatically decrease interference between users. Additionally, the use of virtual cells will improve the signal processing efficiency, where the processing unit will select a virtual cell for each MT dynamically, optimizing by that the transmission jointly with the cell.

1.5 A new look at interference: From multi-user to multi-cell

Densely deployed base stations (BSs) have been proposed to support massive wireless devices and satisfy high-rate expectations. The multiple cellular (multi-cell) technique is a conventional method to cover a large area with multiple user equipment (UEs) [12].

No one can deny that two of main obstacles for wireless communication systems are fading and interference, where fading introduces limitations on propagation and coverage, thus reliability of any point-to-point wireless connection. Interference on the other side, restricts the reusability of the spectral resource (time, frequency slots, codes, etc.) in space, which causes degradation on the overall spectral efficiency. Authors in [12], were discussing two basic scenarios that have been exploited as solution for interference and fading issues for cooperation communication in mobile networks. The first one was implementing the so called “virtual” or “network” MIMO, which consists of maximizing the number of co-channel links that can coexist with acceptable quality of service. In more relevant cases such high SNR regime that can be achieved in a small cell case, the virtual MIMO technique will correspond to the maximization of concurrent interference-free transmissions number which stands for the multiplexing gain of the network, or the number of degrees of freedom as we can find in the information-theoretic references.

In order to mitigate fading issues, a second scenario was deployed, and it is referred as relay-based cooperative communication technique. The relay-based principle consists of filtering out detrimental propagation anomalies from base station to the receiver by making communication occurs through a third-party device that could be a BS or UE that is called a rely. Experiments have shown that the developed relay-based cooperative transmission protocols have introduced an enhancement in point-to-point and point-to-multipoint communications by mitigating fading effects related to both path loss and multipath.

With such results, relay-based technique was exploited by amplify-forward, decode-forward and compress-forward cooperation schemes in order to offer a powerful extra diversity dimension. With a critical position of users at the cell boundaries, where a high inter-cell interference dominates at systemâs performance, relay-based schemes have shown a noticeable increase for the quality of service of these users by exploiting the virtual MIMO technique that improves the reliability and the link-level performance as discussed before.

In the last few years, macroscopic diversity was deployed when multiple base stations were cooperating to provide connectivity for mobile users to insure diversity against long-term and short-term fading. In fact, networks that exploit CDMA allow one mobile user to send and receive signals for more than one base station using soft handoff to experience more possible channels, selecting by this the best link using diversity selection for a given time slot. As a result, selection diversity together with power control allow full frequency reuse in each cell, increasing by this both the coverage and systemâs capacity. However, there is always a price to pay for such an enhancement, since the capacity of CDMA networks becomes critically related to inter-cell interference, so if we will consider a system constituted by only one single cell, the capacity in this case will be much higher if we are considering a system with multi-cell due to interference occurring between the several cells. This degradation in terms of capacity is measured by the so called “f-factor” that will be eliminated later when we will consider the full base stations cooperation.

Considering the downlink case, a full base station cooperation means that all base stations are effectively connected to a central processing unit, which can be seen as a MIMO broadcast channel with distributed antenna since base stations are located in different spots within the system.To talk about base stations cooperation, let us consider uplink communication where a single mobile user is transmitting signals to each base station, these signals are maximal ratio combined that will be processed before decoding.

The uplink scenario can be seen as a MIMO multiple access channel, which allows cooperation between base stations to decode at each user through a single-user matched filter (SUMF) that gathers all signals coming from users' equipment allowing pure interference with no wasted information. Thus, the interfered signals at the “global” decoder shape a sort of useful information, hence interference is exploited, allowing by that cooperation between bases stations. Results had shown that with such a scheme together with power control, the inter-cell interference was faded, means that the “f factor” goes to zero, resulting in equal values for, a systems with multiple cells and another one with only one single cell.

Furthermore, by implementing more multi-user receivers (decorrelator and MMSE receivers) in CDMA networks, it was shown that the same results were obtained, where interference was fully eliminated, and the achievable number of simultaneous connected users is same as if the cells were isolated from each other. However, with base station cooperation the traditional approach of frequency re-use partitioning is suboptimal, since it was shown that Wyner cellular systems models, which are systems with a hexagonal cell shape, that in high SNR regime the capacity of a cellular system with fractional frequency re-use is less than a system with full frequency re-use, by exactly the re-use factor. This is equivalent to saying that full base station cooperation reduces the inter-cell interference penalty (or “f-factor”) to zero.

Although the underlying MIMO theoretic concepts are well understood, cooperative systems are still in their infancy and much further research is required in order to fully understand these systems and to practically achieve the full benefits of multi-base cooperation. Overall, it's true that cooperative MIMO offers additional benefits over simpler beamforming coordination schemes techniques and do not require extra antennas to provide reliability to the communication system, which means less additional costs for multiple-antenna processing, which requires additional hardware and software resources at individual devices, which is the contribution that standard MIMO is introducing. Instead, cooperative MIMO schemes back draw comes with the fact when all devices within the communication system are trying to cooperate with each other or when users/base stations and the central controller are communicating for a given centralized architecture. This excessive number of signals between the cooperating devices or through the central processor will surely introduce a certain delay constraint that increase with the size of the network. Furthermore, data sharing among several BSs and more complex precoding and decoding are required.

Moreover, power control, multi-cell joint scheduling, and rate allocation across the frequency spectrum are serious problems for cooperative MIMO, since they are computationally intractable. On the other side, other researches on interference alignment, network coding, and fractional frequency reuse in OFDMA systems provide a new set of techniques that could be applied to network MIMO in a joint multicell optimization in order to achieve maximum spectral efficiency in a multiple cell network.

Authors in [12], already predict that a future network MIMO system cannot be built according to a centralized architecture, since some research back then have considered the problem of distributing the network-wide optimization problems, so that much of the processing can be done locally, with limited communication between nearby nodes. One option was clustered MCP, in which small clusters of BSs collaborate together on uplink decoding and downlink beamforming. Turbo base stations provide another approach, in which soft information is passed between adjacent BSs, allowing iterative, probabilistic graph-based methods to provide decentralized solutions to similar problems. Still, channel state information acquisition in both base stations or user devices is still a problem, since CSI should be known at each particular node in the network, including information that has been measured at other nodes in the network, because by knowing the channel state information for a given user, we can have a feedback about how much resource we can allocate at the base station in a down link scenario for instance. As a result, missing the CSI for a given node will introduce a blurry idea on gains and resources allocation, creating by this, a fundamental trade-off between cooperation and information exchange between nodes inside the network.

However, with the explosive demand for higher data rates and traffic volume, wireless communication networks are required to provide better coverage, and uniform user performance over a wide coverage area which 5G cannot satisfy. This is because the performance of massive MIMO systems, for instance, is restricted by the inter-cell interference in the cellular network and the cell-edge users suffer significant performance degradation.

1.6 Distributed antenna systems (DAS)

To improve the performance of cell-edge users, distributed antenna systems (DAS) have been proposed to cover the dead spots and offer macro diversity in MIMO systems [14]. The idea behind DAS is to tone down inter-cell interference (ICI), since communication systems, especially cellular ones are always suffering from interference limitations even though if we are increasing the transmit signal power. DAS can also be upgraded by exploiting MIMO communication schemes, since they have shown a significant enhancement in systems performance. Authors in [14] were talking about the architecture of the proposed DAS system, where distributed antenna modules were connected to a “home” base station through a link dedicated only for this communication. Each of these antenna module can exploit several antenna elements and they are geographically distributed at one end of the radio link, while MIMO system was collocated in the other end.

As we discussed before, distributed systems, have the ability to increase system capacity by reducing the overall interference, taking advantage of macro diversity, since base stations are widely spaced from each other. DAS in fact, is benefiting from its distributed nature, which make it easily integrated with recent radio resource management techniques. Additionally, authors were also considering a realistic channel model that was proposed by Wireless-World-Initiative-New-Radio (WINNER II) [15]. This model is a cluster-based stochastic model that includes frequency selectivity together with spatial correlation. Unlike previous studies where they were analyzing a multicell environment DAS performance by implementing a flat-fading channel with a structure that needs extra deployment of antennas inside the cell, authors in [14] are proposing a DAS structure without the need of deploying further base stations, which makes it reliable in terms of implementation costs, especially when the proposed scheme shows good performance in terms of outage capacity and inter-cell interference in a conventional cellular system.

Actually, the proposed design in [14] was a brilliant idea, since they considered a conventional multi cell environment, where each cell has a base station inside, so they were just moving the base station towards the intersection points as described in Figure 1.2 . Then they suggested to divide the omnidirectional antennas in each BS into three parts, where each part will shape the so-called antenna module that will have by its own a number S of antennas. Each antenna module will be pointing in the direction of a cell's center (see Figure 1.3), which means that every cell will be covered

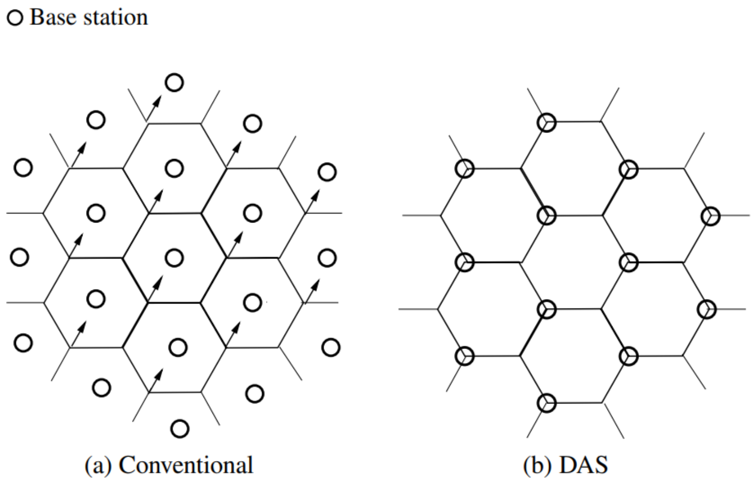

Figure 1.2: Layout of DAS (b) obtained by shifting the cellular layout in the conventional system (a) in the direction of the arrows at the hexagon edges.

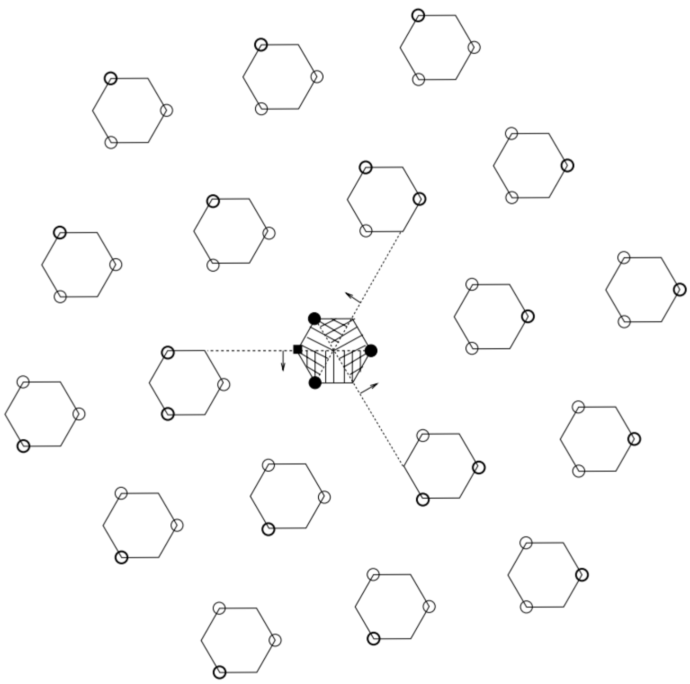

Figure 1.3: Structure of distributed antenna system with 2-tier interference.

by three antenna modules. The BS that is located in the cells' intersection point is now called a Mobile Station (MS) and has as a number of antenna $U = 3S$. The transmit power for each antenna module for a given cell k is $P_i^{(k)}$ that is constrained by the following equation $\sum_{i=1}^{3} P_i^{(k)} = P$, with P is the total transmit power that can be generated by the MS. Since the proposed DAS scheme is uniform and all the cells are identical, they consider the total transmit power for all the MSs are equal. The proposed architecture which is based on moving the BS to a significant critical point, which is the hexagon vertex, and splitting out the mobile station to three antenna modules: the strategy of transmitting signals will be totally different, since each cell is receiving signals from three different antenna modules. Thus, the macro diversity of the DAS will be significantly increased, which implies a soar in the signal power resulting in an important reduction of intercell interference. Moreover, results have shown that SINR and outage capacity in cell boundaries were increased comparing with the conventional cellular system where a base station is in the center. Additionally, comparing throughputs within cells, it was shown that DAS scored much higher and uniform values for all users. As a result, the implemented architecture in [14] proved that DAS has beneficial results that can be exploited in future scenarios.

1.7 Multi-user Cooperative Multiple Points

Following the same path as DAS, to reduced inter-cell interference, network MIMO and coordinated multi-point (CoMP) were proposed in [16] by adding cooperation between the neighboring access points (APs). In fact, several enhanced Node Base Stations (eNBs) are transmitting simultaneously data signal to a user equipment, and can be extended to serve multiple users by exploiting MIMO, since with multiple input-output antennas, a group of users can be served at once according to Space-Division Multiple Access (SDMA) that share the same time and frequency resources among all the served users.

By taking into consideration coordinated multipoint (CoMP) transmission, which was proved to insure a good quality of service to low capacity users while maintaining a high spectral efficiency, a combination between CoMP and MIMO gave rise to multi-user coordinated multipoint (MU-CoMP) that was suggested to improve cellular network performances [16]. Results have shown that CoMP is able to improve conventional cellular system's performance, which is the result of having a number of users grouped as a cluster, sharing by this the same Physical Resource Bloc (PRB). This means that the more users inside the cluster will share the same infrastructure, the better the capacity of our system will be.

In parallel, the concept behind MU-CoMP is to divide a number of given users that chose CoMP to SDMA users groups, so that they will be all served the same PRB. Hence, an effective PRB's allocation between CoMP and non-CoMP users is needed in order to improve the MU-CoMP efficiency. Before dividing users into SDMA groups, users should be split first into CoMP and non-CoMP clusters. Authors in [16] were citing different methods proposed by previous works in order to divide users into CoMP clusters. Some of these works proposed that partition can be basd on on physical distance to eNB criterion. While another one proposed red?? partition according to the received Signal-to-Interference and Noise Ratio (SINR) level, since a user can belong to CoMP transmittion mode if its SINR is inferior to a certain threshold.

Another work suggested a semi-dynamic mode in which a user selects a CoMP transmission mode if it achieves a better average throughput. After splitting out groups into CoMP and non-CoMP clusters, now its time to formulate SDMA groups among CoMP clusters. Authors in [18] proposed a greedy solution where high throughput are grouped together. In [19], the authors proposed a dynamic SDMA users'grouping approach that will insure a kind of SINR balanced partitions, means that SDMA groups will have almost the same SINR.

After discussing some approaches to divide users into CoMP and then into SDMA groups, now it's time to determine how to allocate PRB to ensure system's enhancement. Some previous works have suggested a static PRB allocation scheme, which divides the cell-edge area into two types of zones, and defines a frequency reuse rule to support CoMP transmission for users in each zone [20]. In [21], three kinds of PRB allocation schemes are presented static, semistatic, and hybrid schemes, where they were introducing frequency reuse schemes in MU-CoMP systems to enhance the Inter-Cell Interference Coordination (ICIC).

In parallel, authors in [16] proposed an enhanced solution for bandwidth allocation and SDMA group partition that consists in an adaptive MU-CoMP transmission mode that is based on firstly, identifying in a dynamical way the CoMP and non-CoMP users, to reduce the outage probability in the system at each TTI (Transmit Time Interval). Secondly, the determination of a proper size for each SDMA users group according the traffic load in the cluster. Third, the allocation of the appropriate number of PRBs to each set of users so that the total achieved throughput at the cell border is increased.

To select the number of CoMP and non-CoMP users in the cluster at each TTI and the number of SDMA users group and to better estimate the bandwidth needs of each kind of user and to reduce the outage probability, the users in the cluster are partitioned based on their achievable throughputs rather than on distance or SINR criteria, since by this way we are insuring to have much reliability for performance outcomes. As a result, a user selects a CoMP transmission mode if his throughput under non-CoMP mode is inferior to the one under CoMP mode. Unlike previous studies, where they were considering a semi dynamic approach in which they averaged the achievable throughput over the time observation, in [16] they have introduced a dynamic approach since the selection is achieved at each TTI. Moreover, a bias factor δ was introduced so that more users are encouraged to select CoMP transmission mode. By implementing the bias factor, the same PRB will be served for a CoMP group that will be more loaded, which implies a reduction in the outage probability of the system. By introducing this bias factor, the variation of the traffic during the different TTI, and also the total load in the cluster is considered. The bias factor δ $(0 < \delta < 1)$ was introduced in a way that it could be set by eNBs according to the number of users in the cluster and their total required throughput. Note that by using the bias factor more users are encouraged to select the CoMP mode, while more users in CoMP implies that SDMA groups can have more users, which might prevent achieving higher throughput, due to high mutual interference. Hence, a

SDMA group size should be determined in a way to avoid co-interference between users, and it would be a great idea to keep the SDMA group size as low as possible. Moreover, increasing the number of CoMP users implies increase of PRB scheduling for these users, means that less PRB will be allocated for non-CoMP users, which results using a higher outage probability. For this reason, authors in [16] proposed a dynamic CoMP transmission selection scheme, where the size of SDMA users group adaptively varies according to the resulting outage probability. At each TTI, for each total number of users in the cluster, a size U of all SDMA users'group in cluster was initialized, they estimate the resulting outage probability. The SDMA size U is keep increasing it reaches a maximum size $Umax$ above which, a disruptive interference will be created. As a next step, when the number of CoMP users as well as the size of the SDMA users'group is determined by applying the former phase total number of available PRBs is divided between the CoMP and CoMP users according to their required throughput.

However simulation results have shown that for a bias factor δ and for a certain number of users per cell, increasing of the SDMA users group size U will generate an increase of system's outage probability. In fact, increasing the number of users within a SDMA group will bring drawbacks, since interference between the users co-scheduled on the same PRBs will surely occur, also the transmit power allocated by each cooperative eNB to each CoMP user within a SDMA users'group will be reduced.Thus, to improve the outage probability, the SDMA users'group size should thus be small.

From the bias factor perspective, the higher the bias factor, the greater the number of CoMP users in the cluster, which means that the number of served users in the system will increase. As a result, the outage probability of the system decreases. However, it was shown by introducing a bias factor, outage probability can decrease up to 20% as compared to static scheme without an excessive loss of user's quality of service. On the other hand, simulation results also showed that the achieved total throughput of CoMP users at the cell edge is considerably enhanced for a given outage probability in the system.

1.8 Beyond 5G, towards 6G

High bit rates, uniform user performance over the coverage area, ultra-low latencies, great energy efficiency, robustness against blocking and jamming, and wireless charging are actual feature that that needed to be satisfied for today's and especially for future wireless communication. Since 5G communications networks are not covering many of them [13], because they are basically relying on millimeter wave (mmWave) frequencies since they are providing large bandwidths that were not used before, and that can be translated into higher bit rates, studies and experiments have shown that those frequencies are suffering from high signal blockage due to the fact that that wavelengths are in order of some millimeters which makes it hard for long distances propagation. For sub-6GHz spectrum, even mmWave will provide 10 times more bandwidth, the bit rate might not increase if data signals can be multiplexed 10 times fewer. This problem become even more worse for sub-teraherts (THz) bands that were studied recently for beyond 5G. Hence, intensive studies should be done for new multiple antenna technologies that will help overcoming this problem of mmWaves in sub-6GHz and higher bands together with considering both time-division duplex (TDD) and frequency-division duplex (FDD) modes. Actually, current multiple antenna schemes were investigated for beyond 5G deployment that will be mainly consist of free-cell massive MIMO, beam space massive MIMO and intelligent reflecting surfaces (IRS).

1.8.1 Cell-free massive MIMO

Itâs true that 5G cellular systems have shown a significant improvement in terms data rates and traffic volumes and low latency for data transmission comparing to legacy cellular technologies. Unfortunately, these improvements are primarily achieved by UEs that are located next to cell centers that can easily perform operations, thanks to their lower interference levels and higher achievable data rates, while other users suffer from inter-cell interference and handover issues due to their location that is close to cells borders, where most of the traffic congestion is happening.

The 95%-likely user data rates which can be guaranteed to 95% of the users and that defines the user-experienced performance, is still low in 5G networks. Consequently, beyond 5G systems should implement the cell-free architecture, where there are no cell borders that will cause the inter-cell interference and handover issues. Earlier solutions were given by previous architectures that we discuss, i,e. DAS, CoMP, and network MIMO. However, some challenges might occur that are related to huge computational complexity together with massive fronthaul signaling for CSI and data sharing. To tackle this issue, a possible solution consists of dividing the network into disjoint clusters containing a few neighboring, so that only those need to exchange CSI and data. This network-centric approach can provide some performance gains, but only partially addresses the interference and handover issues, which remain along the cluster edges.

To tackle interference and handover issues, a cell-free communication architecture was introduced in [22] that could be seen as a network with only one huge cell, thus getting rid of inter-cell interference and handovers issues. Moreover, each user will be served by multiple access points (APs) or base stations (BSs) that can reach it with non-negligible interference. This in fact, creates a user-centric network, where each AP collaborates with different sets of APs when serving different UEs. Hence,is the UEs select which set of APs will better serve them, not the network. To enable such a connection, the APs are assumed to be connected via fronthaul to cloud-edge processors that take care of data encoding and decoding. These are often called central processing units (CPUs) and the structure is like the one of cloud radio access network (C-RAN). In order to inspect the performance of cell-free massive MIMO, it would be a great idea if we will compare it with a cellular network with the same set of APs, but where each user is only served by one AP (i.e., a small-cell network). It was shown that cell-free massive MIMO can achieve almost five times improvement in terms of 95%-likely per-user spectral efficiency [23]. Another relevant comparison will be between conventional cellular massive MIMO, consisting of a relatively small number of APs, each equipped with a large number of antennas. Results have shown that cell-free massive MIMO can substantially improve the

95%-likely per-user spectral efficiency, while cellular massive MIMO is the preferred choice for cell-center UEs. This emphasizes the fact that cell-free architecture is not only about achieving higher peak performance, but also about uniform performance within the coverage area. Moreover, the energy efficiency of cell-free massive MIMO was considered in [24], which showed that it can improve the energy efficiency (measured in bit/Joule) by nearly ten times compared to cellular massive MIMO. As a result, there are two main reasons to adopt cell-free massive MIMO in beyond 5G networks, the first one is the increased 95%-likely spectral efficiency, and the second one is the higher energy efficiency.

1.8.2 Intelligent reflected surfaces (IRS)

No one can deny that MIMO technology brought significant improvements for systems'performance in terms of spectral efficiency. However, it was shown that by increasing the number of antennas, data rates go higher as well with a linear shape. The drawback is that while increasing the number of antennas, energy efficiency (bit/Joule) goes up too but this time in a logarithmical way. As a result, several researches were conducted in order to maximize the energy efficiency of MIMO systems by optimizing power allocation and network topology [25] [26], where they found out that an optimal solution for such a design (taking into consideration the trade-off between data rates and energy consumption), will require implementation of many hardware components,making it costly, hence posing a financial constraint. Furthermore, in order to realize economically sustainable wireless communication networks that would respect at once economical constraints, energy and spectral efficiency, a new MIMO antenna architecture is introduced, and it is called intelligent reflecting surfaces or software controlled meta-surfaces [27].

The concept of introducing IRS is able to manipulate phenomena that governs the propagation of electromagnetic waves for a given wireless medium, such as diffractions, reflections, shadowing and pathlosses before reaching the receiver rather than changing their behavior, benefiting from existed techniques such as beamforming, diversity and channel coding, thus improving systemsâ performance. Actually, IRS builds on the classical concept of reconfigurable reflectarrays [28] with an enhancement of having real-time control and reconfigurability. In fact, an IRS is a metasurface consisting of a large set of tiny elements that diffusely reflects incoming signals in a controllable way. IRS is a flat finite-sized surface that reflects the incoming wave in the main direction determined by Snell's law, with a beamwidth that is inversely proportional to the size of the surface relative to the wavelength.

We can set a correspondence between the IRS and a specular mirror, but instead of reflecting rays that fall within the visible spectrum without any control of the reflective beam, the IRS can control the direction of the reflected signal since it is composed of tiny meta-atoms whose size is in the order of sub-wavelengths, and each meta-atom is introducing a distinct phase shift that controls the angle of departure (AoD) of the incident wave on the IRS surface. Theoretically, the reflection process of the IRS should be done in a continuous way, but due to practical implementation issues, this is done in a discrete way. As a result, the joint effect of all phase shifts is giving rise to a reflected beam in a selected direction.

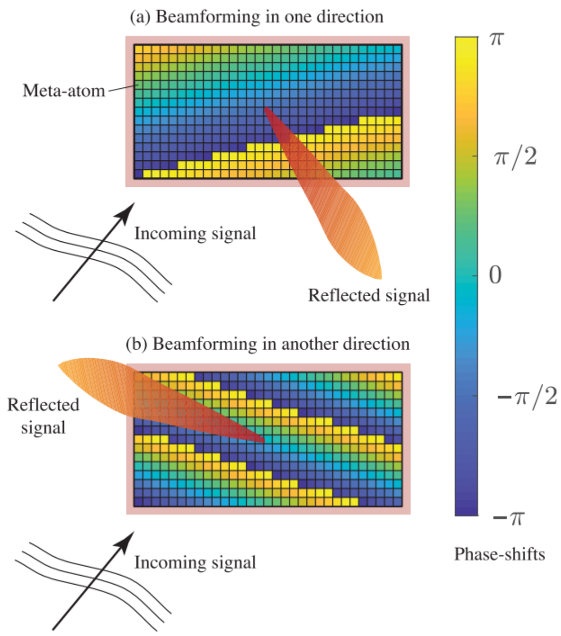

Figure 1.4: IRS meta-atoms are beamforming signals according to given phase shifts according to the color diagram .

Figure 1.4 is illustrating how the sort of “beamforming” that an IRS is introducing can happen, by deploying different phase shift patterns of each meta-atom that gives as an output a “beamformed” signal towards a specific direction in the far field or simply by focusing the signal if the intended user is close to the IRS in the near field. To tackle the energy efficiency requirements, IRS is considered one of the best solutions so far especially in the energy-limited systems. As an example, with an IRS that consists of 8x8 mm meta-atoms, the energy consumption is about 125mW$/m^2$, which is lower comparing to distributed APs or CoMP. In fact, the IRS is not supposed to replace or compete with conventional massive MIMO technology, but rather complement it.

Figure 1.5.a describes the deployment of an IRS in a conventional MIMO

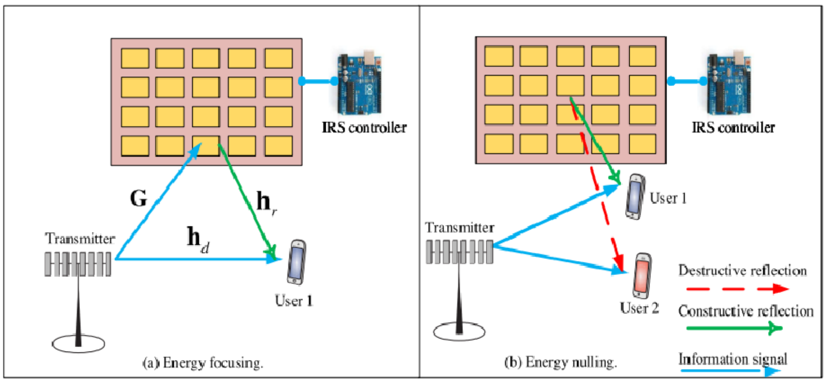

Figure 1.5: IRS implementing energy focusing and energy nulling

system, where a multi-antenna base station wants to transmit signals to user 1. By considering the direct path, the transmitter will perform beamforming in order to improve the received signal at the user. In parallel, the radiated signal from the transmitter could be received by the IRS as well, due to the broadcast nature of the wireless channels. On the IRS level, an IRS controller will configure in a proper way the phase shifts for every meta-atom that will produce individual scattered signals that will be jointly gathered, producing by this a coherent reflected beam that is focused towards the user. Note that, the more IRS elements, the better it is, since the larger number of meta-atoms on the IRS surface the more narrower the reflected beam will be, which is known as energy focusing [29].

Considering, Figure 1.5.b and by assuming a MIMO system where there is no direct path between the multi-antenna transmitter and the users due to high link blockage, to receive signals it is crucial to go through the IRS.

Let's consider the scenario where the transmitter wants to serve only user 1 for a certain time slot, and user 2 should not be able to decode the transmitted information due to security reasons, the IRS controller then should configure the IRS so that the elements will introduce phase shifts that will null the reflected signal towards user 2 or what we called destructive reflection towards user 2. At the same time, user 1 will benefit from the same configuration to receive the information benefiting from the constructive reflection. Even though it can be considered as a passive device, actually it can operate naturally in a full-duplex without the need of costly self-interference cancellation.

By exploiting the constructive and destructive concepts, IRSs are expected to have wide applications in various communication systems involving interference management, coverage extension, and capacity improvement, such as in wireless-powered communication systems, cognitive radio networks,and physical layer security systems. Furthermore, an IRS can be of thin and comfortable material, allowing for nearly invisible deployment on building facades and interior walls. Hence, once a conventional network has been deployed, one or multiple IRSs can be flexibly deployed to mitigate coverage holes that have been detected or to provide additional capacity in areas where that is needed.

1.8.3 Beamspace MIMO

The more antennas are used in a MIMO transceiver, and the higher the carrier frequency and bandwidth are, and the more complicated the implementation becomes. One way to reduce the implementation complexity, without sacrificing too much in performance or operational flexibility is to utilize the spatial structure of the channels and transceiver hardware. In this section, we describe beamspace massive MIMO, which is the general concept that underpins hybrid beamforming and its future successors. We particularly focus on recent progress and open problems related to using lens arrays for beamspace massive MIMO.

In the last decades, open-loop techniques were adopted in order to achieve single-user MIMO performance. Open loop means that transmitter is able to transmit signal without considering channel state information (CSI) from its side. The most popular open-loop techniques are diversity techniques such as space-time block codes, space-time trellis codes and multiplexing techniques (spatial multiplexing). The performance of these techniques is somehow suboptimal, since the transmission is done without any CSI. Later in 2000s, linear precoding was adopted for single-user MIMO, where a multiple antenna open-loop signal is including sort of channel information, and this is done by multiplying the signal by a precoding matrix before transmission. [30].

At that time, commercially MIMO transmitters had less than eight antennas and linear precoding was implemented using direct digital implementation. For instance, LTE Release 8 systems had only four antennas at maximum for each base station. Thus, direct digital processing of precoding was so practical because it is cost-effective for small arrays due to high-resolution analog-to-digital converter (ADC) at each transmit element. In this kind of implementation, signal transmission can be easily done by multiplying it by single matrix due to the constraint of antenna number at the transmitter. Consequently, linear precoding was widely implemented in multiple standards including 4G Long-Term Evolution (LTE), 5G NR, and versions of IEEE 802.11 (WIFI).

Recently, due to the high number of antenna used in mmWave and massive MIMO transmitters, it expected that number of antenna will be even much larger in sub-6 GHz , sub-THz and 6G systems, thus the implementation of linear precoding should be taken into consideration for further studies. Because of the high number of antenna, the dimension of precoding matrix will be significantly large, it would be even worse if we are considering the deployment of other techniques such as hybrid digital-analog arrays that have unique hardware characteristics, thus it will make it impractical to keep maintaining linear coding algorithms for signal transmission. For this reason, beamspace schemes should be adopted for 5G and beyond 5G systems. Beamspace indeed, will be using a subspace approach that is based on virtual or effective channels using the idea of dual-codebook precoding. For instance, Release 10 of LTE-A was first including a dual codebook approach for eight-antenna downlink precoding, where a first matrix (called the wideband matrix), was selected to adapt to spatial characteristics of the channel a second matrix was then chosen conditioned on the first.

In a CoMP system for instance, a UE is receiving signals from multiple distributed transmission points, which could be utilizing diverse forms of precoding and multiuser transmission. At the receiver side, in order to not overwhelm the UE by high computational operations, the beamspace consists of configuring the UE with K reference signals and CSI feedback reports.

The multiple transmission points could send reference signals over each of the possible first precoders $\boldsymbol{W}_1[1], ..., \boldsymbol{W}_1[K]$. The sounded precoder $\boldsymbol{W}_1[K]$ would have a corresponding virtual channel $\boldsymbol{H}_\mu[K]$. Then, the user would send feedback for selection of the precoder, through the corresponding CSI feedback reports, for each of the respective virtual channels. Thus, the user is not required to know $\boldsymbol{W}_1[1], ..., \boldsymbol{W}_1[K]$, but instead it is only required to know the number of reference signals, CSI feedback reports, and the corresponding configuration information for each one of both. In 3GPP, they were already discussing some practical scenarios where to use of beamspace such as in hybrid beamforming and precoding at mmWave frequencies [31].

Chapter 2

Cell-Free Resource Allocation

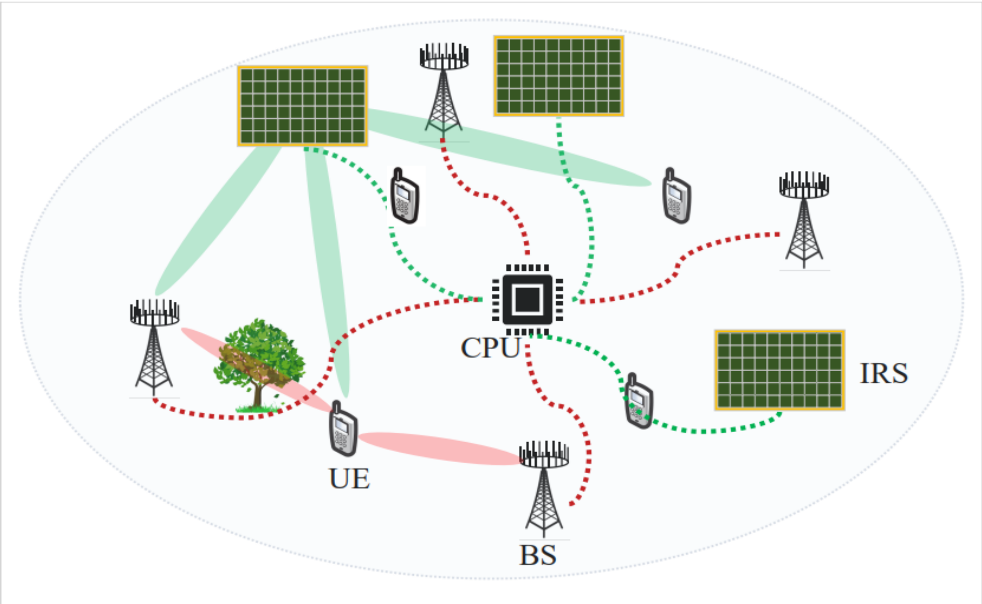

Figure 2.1: IRS-assisted cell free MIMO system model

2.1 System Model

As described in Figure 2.1, the system represents a distributed multiple IRSs assisted cell free MIMO downlink communication systems, constituted by K UEs that are served by L distributed BSs and R distributed IRSs which are linked to a CPU, where each BS, IRS and UE are equipped with N_{T} antennas, N phase shifts and N_{R} antennas, respectively.

In order to transmit and receive signals, both BSs and UEs are exploiting electronically steerable uniform linear antennas arrays (ULA) to electronically direct a beam, stressing the fact that data flows as independent streams from each element of the array at the BS towards each element of the array at the UE . Consequently, we are defining the following vectors that will describe the communication among each BS and UE.

- $\boldsymbol{s}_k$ is the data symbol vector that will be received at the k^{th} UE.
- $\boldsymbol{W}_{\mathrm{l,k}} \in \mathbb{C}^{N_{\mathrm{T}} \times N_{\mathrm{R}}}$ is the corresponding active transmit beamforming matrix from the l^{th} BS to the k^{th} UE.
- $\boldsymbol{Q}_{\mathrm{k}} \in \mathbb{C}^{N_{\mathrm{R}} \times N_{\mathrm{T}}}$ is the beamforming matrix at the k^{th} UE.
- $\boldsymbol{D}_{\mathrm{l,k}} \in \mathbb{C}^{N_{\mathrm{R}} \times N_{\mathrm{T}}}$ describes the direct channel from l^{th} BS to k^{th} UE.

Additionally, we are exploiting the technology introduced by IRSs in order to make a UE have more options to be connected by creating new sets of beams that can be linked to, especially in the case where an obstacle is placed between our BS and UE which may result signal degradation or even signal lost. Hence, by exploiting the IRS we are improving beams availability for our UE which means high signal powers, high throughput and low latency, especially if the UE is located in a far distance from our BS. Moreover, an IRS is composed of by N passive phase shifts, each of these phase shifts can reconfigure the incident signals coming from the BS to other desired directions with considrable array gains, that is given by $\boldsymbol{\Theta}_r = \alpha \mathrm{diag}(\mathrm{e}^{\mathrm{j}\phi_{\mathrm{r},1}}, \mathrm{e}^{\mathrm{j}\phi_{\mathrm{r},2}}..., \mathrm{e}^{\mathrm{j}\phi_{\mathrm{r},\mathrm{N}}})$, which describes the passive reflecting beamforming matrix at the r^th IRS , while $\phi_{r,n} \in [0, 2\pi]$ denotes the phase of the n^{th} phase shift of the r^{th} IRS.

Besides, each phase shift can change the phase of the incident signal in a discrete way, means that we can have a discrete number of possible configurations, each configuration can evolves a discrete set of reflected beams. By implementing the IRS, two additional channels will be added to our system,

- $\boldsymbol{G}_{\mathrm{r,k}} \in \mathbb{C}^{N_{\mathrm{R}} \times \phi_{\mathrm{r}}}$ which is the channel between r^{th} IRS and k^{th} UE.
- $\boldsymbol{Z}_{\mathrm{l,r}} \in \mathbb{C}^{\phi_{\mathrm{r}} . N_{\mathrm{T}}}$ that is the channel between l^{th} BS and r^{th} IRS.

However the gains achieved by IRSs are critically depend on the perfect channel state information (CSI), which is challenging to acquire due to the passive nature of IRSs together with the fact that they cannot sense the channel. Yet, the channels in IRS-assisted systems are estimated at the BSs through uplink pilots, and the so-obtained CSI are used to procode the transmitting data in the downlink, with the aid of a smart IRS controller, which can design the passive reflective beamforming to achieve several objectives as transmitting power minimization,energy efficient maximization and so on .

Hence, the system's overall channel $\boldsymbol{H}_{\mathrm{l,k}} \in \mathbb{C}^{N_{\mathrm{R}} \times N_{\mathrm{T}}}$ can be expressed as the following

$$\boldsymbol{H}_{l,k}^{H} = \boldsymbol{D}_{l,k}^{H} + \sum_{r=1}^{R} \boldsymbol{G}_{r,k}^{H} \boldsymbol{\Theta}_{r} \boldsymbol{Z}_{l,r} \tag{2.1}$$

Moreover, by considering the noise at the k^{th} UE $\boldsymbol{n}_{\mathrm{k}} \in \mathbb{C}^{N_{\mathrm{R}} \times 1}$, which can be seen as a complex circularly symmetric Gaussian (CSCG) white noise matrix, the received signal at the k^{th} UE is given by

$$\boldsymbol{y}_{k} = \boldsymbol{Q}_{k}(\sum_{l=1}^{L} \boldsymbol{H}_{l,k} \boldsymbol{W}_{l,k}^{H} \boldsymbol{s}_{k} + \sum_{l=1}^{L} \sum_{l=1, i \neq k}^{K} \boldsymbol{H}_{l,k} \boldsymbol{W}_{l,i}^{H} \boldsymbol{s}_{i} + \boldsymbol{n}_{k}), \forall k \in K \tag{2.2}$$

Notes :

- the signal power loss is caused by the signal absorption of the phase shifts.

- The noise $\boldsymbol{n}_{k}$ at k^{th} UE, $\boldsymbol{n}_{\mathrm{k}} \sim \mathcal{N}(0, \boldsymbol{I}_{\mathrm{n}})$, is Gaussian distributed with zero-mean entries. Hence, it is associated with a correlation matrix $\boldsymbol{R}_{n_{k}} = \sigma^{2} \boldsymbol{I}_{N_{R}} \in \mathbb{C}^{N_{\mathrm{R}} . N_{\mathrm{R}}}$, where σ^{2} and $\boldsymbol{I}_{N_{R}}$ are the power noise and identity matrix respectively.

2.1.1 Network Capacity

In order to proceed with our network capacity, knowing that data flows as independent streams from each antenna at l^{th} BS towards each antenna at k^{th} UE, first let us compute the maximum data rate that can be achieved by all UEs in the network.Hence, let us define the following scalars and matrices

$$A_{k} = \boldsymbol{Q}_{k}^{H} \sum_{l=1}^{L} \boldsymbol{H}_{l,k} \boldsymbol{W}_{l,k} \tag{2.3}$$

is the signal received without interference at the k^{th} UE

$$B_{k,i} = \sum_{l=1}^{L} \boldsymbol{Q}_k^H \boldsymbol{H}_{l,k} \boldsymbol{W}_{l,i} \tag{2.4}$$

describes the interfering signal between the $k^t h$ and the i^{th} UEs.

$$\boldsymbol{C}_k = [B_{k,1}, ..., B_{k,k-1}, B_{k,k+1}, ..., B_{k,K}] \tag{2.5}$$

is a vector that stores all the interfering signals between users and the k^{th} UE.

Additionally, let us define also the column vector of data symbols for all the users except the k^{th} user :

$$\bar{\boldsymbol{s}}_{\boldsymbol{k}} = [\boldsymbol{s}_1^T, ..., \boldsymbol{s}_{k-1}^T, \boldsymbol{s}_{k+1}^T, ..., \boldsymbol{s}_K^T]^T \tag{2.6}$$

Then the received signal at the k^{th} UE given by (2.2) can be written as

$$y_k = A_k s_k + \boldsymbol{C}_k \bar{\boldsymbol{s}}_k + \boldsymbol{Q}_k^H \boldsymbol{n}_k = A_k s_k + w_k \tag{2.7}$$

where, $w_k = \boldsymbol{C}_k \bar{\boldsymbol{s}}_k + \boldsymbol{Q}_k^H \boldsymbol{n}_k$ is the vector of noise and interference. Assuming $\boldsymbol{s}_k$ is a zero-mean Gaussian with independent power P_k entries, the capacity of the our system described in Figure 2.1 is given by

$$c_k = \log_2 \left(1 + \frac{P_k |A_k|^2}{\sum_{i=1, i \neq k}^{K} |(\boldsymbol{C}_{\boldsymbol{k}})_i|^2 P_i + \sum_{j=1}^{N_R} |(\boldsymbol{Q}_k)_j|^2 {\sigma_n}^2} \right) \tag{2.8}$$

2.1.2 Problem Formulation

After defining our system model, and in order to establish a communication between k^{th} UE and l^{th} BS, it will be crucial to define a set of possible configurations $C_{l,k}$ from which the k^{th} user will be capable to pick up a g_k configuration to communicate with the l^{th} BS. Moreover, each configuration g_k will introduce

- $\mathbb{W} = \{\boldsymbol{W_1}, \boldsymbol{W_2}, ..., \boldsymbol{W_{M_T}}\}$: is the codebook at the l^{th} BS, representing a finite set that contains $\mathrm{M_T}$ as the maximum number of beamforming vectors, which is equal to the number of steering directions at the l^{th} BS.

- $\mathbb{Q} = \{\boldsymbol{Q_1}, \boldsymbol{Q_2}, ..., \boldsymbol{Q_{M_R}}\}$: is the codebook at the k^{th} UE, representing a finite set that contains M_R as the maximum number of beamforming vectors, which equal to the number of steering direction at the k^{th} UE.

- $\Phi = \{\boldsymbol{\Theta_1}, \boldsymbol{\Theta_2}, ..., \boldsymbol{\Theta_n}\}$: is the codebook at the r^{th} IRS, representing a finite set that contains n as the maximum number of phase shifts.

Stressing the fact that each UE may have a different codebook, i,e different configuration, from other UEs due to different positioning, computational powers and so on, our problem will be mainly focusing on choosing the best configuration that will maximize the total capacity of the system, by maximizing each UE's SINR given by 2.8. Our problem is then described by

$$\max_{\boldsymbol{Q},\boldsymbol{W}/\boldsymbol{\Theta}} c_k \tag{2.9}$$

2.2 Proposed Solution

Our problem stated in (2.9) is a discrete one, since we have to choose the best beamformers from discrete sets $\mathbb{Q}$, $\mathbb{W}$, or Φ (if exists), in a way to maximize $\boldsymbol{Q}$, $\boldsymbol{W}$, or $\boldsymbol{\Theta}$, for each user k. Discrete problems are usually hard to deal with. Thus, we are proposing an exhaustive search algorithm, that runs over all possible codewords $\boldsymbol{Q}$, $\boldsymbol{W}$, and $\boldsymbol{\Theta}$ (in case of IRS deployment), and picks up the best ones that maximize the SINR given by (2.8), for a given user k. Hence, allowing maximization of our system's capacity.

2.3 Related Works

The performance of conjugate beamforming (CB) along with a pilot assignment algorithm has been investigated in [23] to combat pilot contamination in a cell-free massive MIMO network. In order to boost system throughput, a max- min power allocation was considered. However, the optimal solution to the power allocation problem involves high computational complexity, due to the non-convexity of the optimization problem. To address this issue, [32] proposed a power allocation algorithm with a trade-off between low complexity and moderate decrease in performance. The authors in [32] further combined the max-min power allocation algorithm with a linear zero-forcing (ZF) precoder to tackle the high inter-user interference in CB technique. These studies restricted their discussion to the simplest linear precoding schemes which are CB and ZF, and did not design an optimal beamformer that ensures uniformly good service over all the coverage area.

Authors in [33] proposed a novel algorithm for downlink resource allocation in order to secure a uniform user experience across the network along with the improved system performance, the problem of interest was to maximaize the minimum achievable rate of each user in a cell-free massive MIMO network in terms of resource allocation, especially precoding vectors and power allocation. They have simulated a cell-free massive MIMO network in which M APs and K single antenna UEs are randomly distributed over a square of size $1000 \times 1000m^2$, where a three-slope path loss model along with an uncorrelated shadowing model were implemented. They also assumed that the pilot sequences have the same length as the number of UEs $\tau = K$.

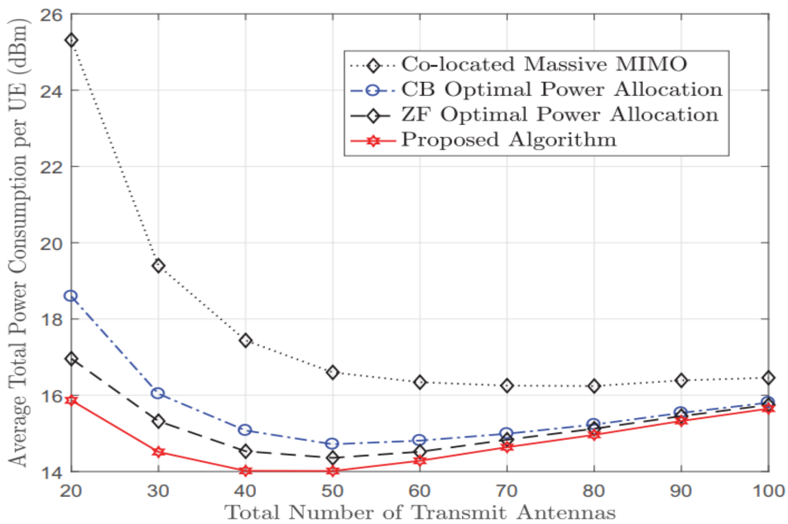

Figure 2.2: Average total power consumption versus total number of transmit antennas in cell-free massive MIMO network

In Figure 2.2 and Figure 2.3,they were comparing the average total power allocation consumption per user in dbm, between co-located massive MIMO, cell free CB with optimal power allocation, ZF with optimal power allocation

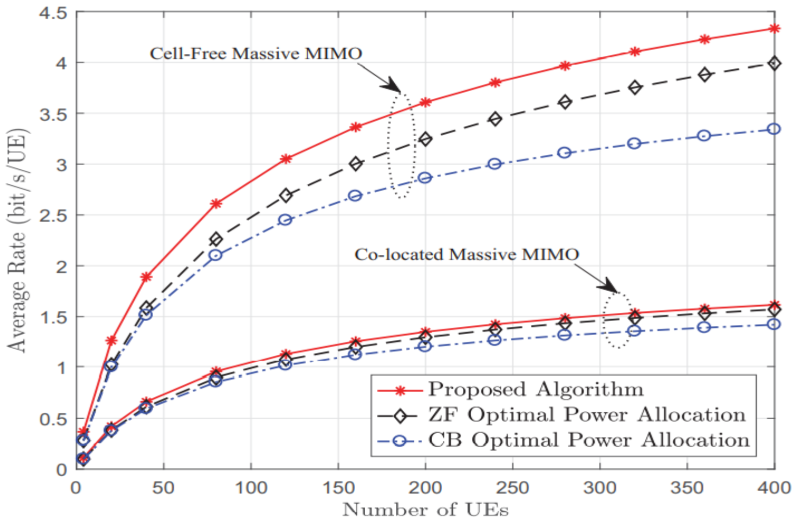

Figure 2.3: Downlink average rate per UE versus total number of UEs in both cell-free and co-located massive MIMO networks

and the proposed algorithm. It turns out that by designing the beamforming and power allocation vectors according to the proposed algorithm in [33] provides better energy efficiency. Also by considering the proposed solution, it was shown that for both co-located massive MIMO systems and cell-free massive MIMO systems, the proposed algorithm tends to have higher bit rates comparing to ZF and CB algorithnms.

Chapter 3

Numerical Results

3.1 Code Organization

First of all, we are randomly generating in a $500m \times 500m$ square, a number L and K of BSs and UEs respectively, that are equipped by uniform linear arrays (ULA). Every array contains N_T and N_R number of antennas for both BS and UE respectively. Then, we are creating codebooks $\mathbb{W}$ and $\mathbb{Q}$ that containing a certain number of $\boldsymbol{W}$ and $\boldsymbol{Q}$ codewords respectively. Each codeword in $\mathbb{W}$ is representing a matrix of size $N_T \times 1$. Similarly, every codeword in $\mathbb{Q}$ is representing a $N_R \times 1$ matrix. The total number of codewords in each codebook is equal to the number of steering directions. Hence each codeword is representing in fact a beam that is steered towards a direction.

Additionally, by deciding the number of IRS elements (meta-atoms), together with the height, we are generating the codebook Φ with a certain number of codewords that is equal to the number of steering directions which is the number of elements or number of phase-shifts. We are then introducing a number R of IRSs with random positions to our system to fit together with BSs and UEs. Now, with the existence of IRS, we should also generate channels $\boldsymbol{Z_{l,r}}$ between l^{th} BS and r^th IRS, and channels $\boldsymbol{G_{r,k}}$ between r^{th} IRS and k^{th} user. Finally, in the same way we are implementing equations (2.3), (2.4), (2.5) and (2.8) to have spectral efficiencies for each user k .

Afterwords, we are generating realistic direct channels between every single BS and every single UE according, according to 3GPP TR 38.901/900 protocols. Channel generation we be then dependent on :

- Number of antennas at the transmitter N_T.
- Number of antennas at the receiver N_R.
- BS and UE coordinates.
- Boolean conditions on shadowing and Line of Sight (LoS).

Furthermore, we are considering our 3GPP channels according to the "UMa" scenario (3GPP TR 38.901, Tab 7.5-6 Part-1, NOTE 6), where considering mmWaves with frequencies smaller than 6 GHz (sub-6GHz).However, further parameters for this scenario are given as the following :

- Carrier frequency : $f_c = 26GHz$.
- Antennas are considered isotropic, which implies that field radiation pattern is set to 1.
- Antenna spacing in wavelength units equal to 0.5 .

- All the nodes are in static state (no motion).
- BSs and UEs having the same height that should not be below 10 meters.

Let $\boldsymbol{H_{l,k}}$ be the channel matrix between every l^{th} BS and k^{th} UE. The result will be a set of matrices, where every matrix is of size $N_R \times N_T$. Now, all ingredients are ready to start computing signal to noise and interference ratios (SINRs) according to (2.3), (2.4) and (2.5) and implementing (2.8) in order to get different values of capacities for each user k .

3.2 Results Discussion

3.1 is representing capacity evolution with respect to the number of users, where we can notice that the capacity for 8 users with 16 transmitting antennas at each BS and 8 antennas at each UE is higher when BS are equipped with only 8 antenna and 4 antennas at UE instead of 8. However, in both cases the capacity is getting more higher values when the number of users is increased.

Instead, 3.2 is describing the CDF function of capacity while performing 100 simulations for two scenarios ($N_T = 16, N_R = 8 and N_T = 8, N_R = 4$), in each scenario we examined the CDF function for 4 users. Let's consider the case where we are comparing 50% of performed simulation and the capacity of each user.

- As first perspective: comparing the four users for the first scenario ($N_T = 16, N_R = 8$), we are noticing that the capacity of these users are

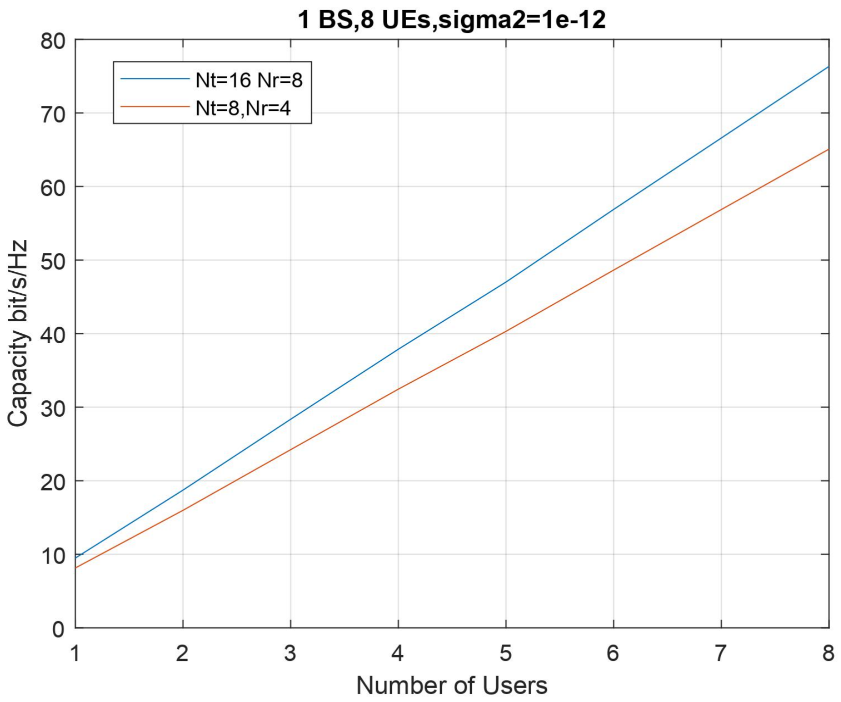

Figure 3.1: Capacity as a function of different numbers of antenna at BS and number of users.

much higher than the ones considered in the second scenario ($N_T = 8, N_R = 4$).

- As second perspective: comparing two users in the same scenario, will give us an idea about the positioning of that UE, for instance comparing UE1 and UE2 from scenario1, we can clearly see that capacity of UE1 is higher than UE2 regarding 50% of performed simulations, which means that for half of simulations UE1 was closer form BS than UE2.

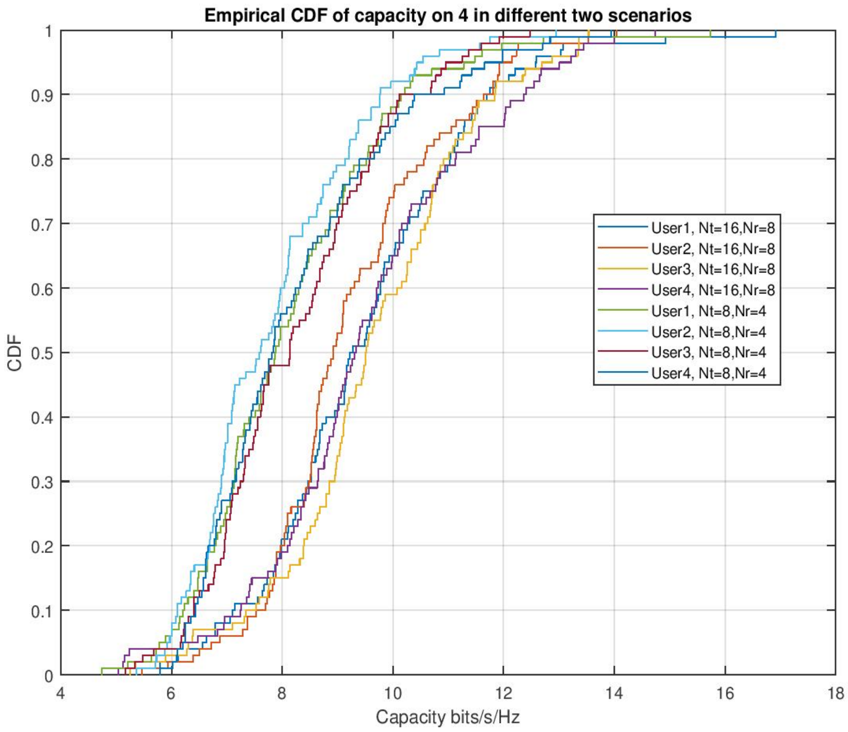

Figure 3.2: Cumulative distribution function of four users in two different scenarios.

By analyzing 3.3 , we can easily notice the fact that when we are increasing the number of users, we can get higher values of capacity for the whole system. In fact, while comparing with 3.1 we can see that a system's capacity with 8 users that reaches almost 65 bit/s/Hz, instead a system's capacity with 10 users reaching almost 80 bit/s/Hz.

However, 3.4 is stressing the fact that when we are increasing the number of BSs and maintaining the same number of UEs, the spectral efficiency also increases, since with more bases stations, users will have more available links to exchange data, hence system's capacity is improved.

Furthermore, 3.5 is describing the improvement of system's capacity while

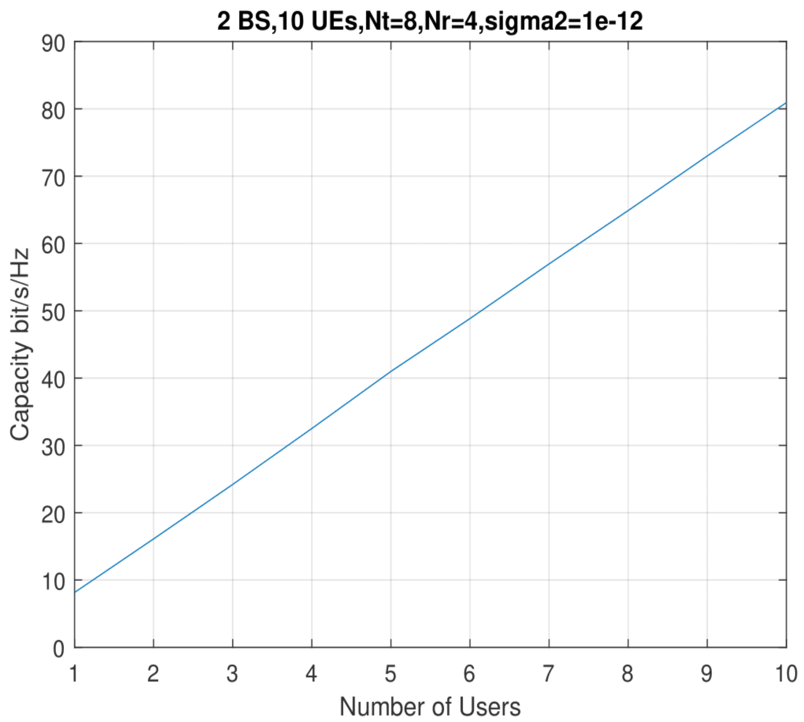

Figure 3.3: Capacity increases with more user equipments

maintaining the same transmitting and receiving parameters but with the change of steering directions number. We can notice that, by increasing the number of steering directions (more possible choices to make connection between UEs and BSs), the capacity is getting higher, and of course the values obtained in first scenario still higher than in the second one, thanks to the higher number of antennas at both BS and UE.

By introducing one or multiple IRSs in an environment where all devices are connected throught Line of Sight, we can barely see the contribution of the IRS in terms of capacity (see Figure 3.6), since the IRS is a passive device : thus, especially if there are no existing blockages for users, the IRS is almost useless to improve the system's capacity. Also we can notice that

Figure 3.4: Capacity improvement with higher number of base stations

although system's capacity did not improve, an IRS would never has a side effect on the system, in other words, capacity is not reduced by using the IRS in LoS a scenario.

In Fig.3.7, we have increased the number of BSs to three and we are considering the scenarios to test the evidence of including IRS to our system.

- First, we can clearly see degradation of our system's capacity by considering the NLoS scenario when there is no implementation of IRS, since we have chosen to introduce obstacles in direct paths between nodes to verify if the total spectral efficiency will decrease, which is in fact happened.

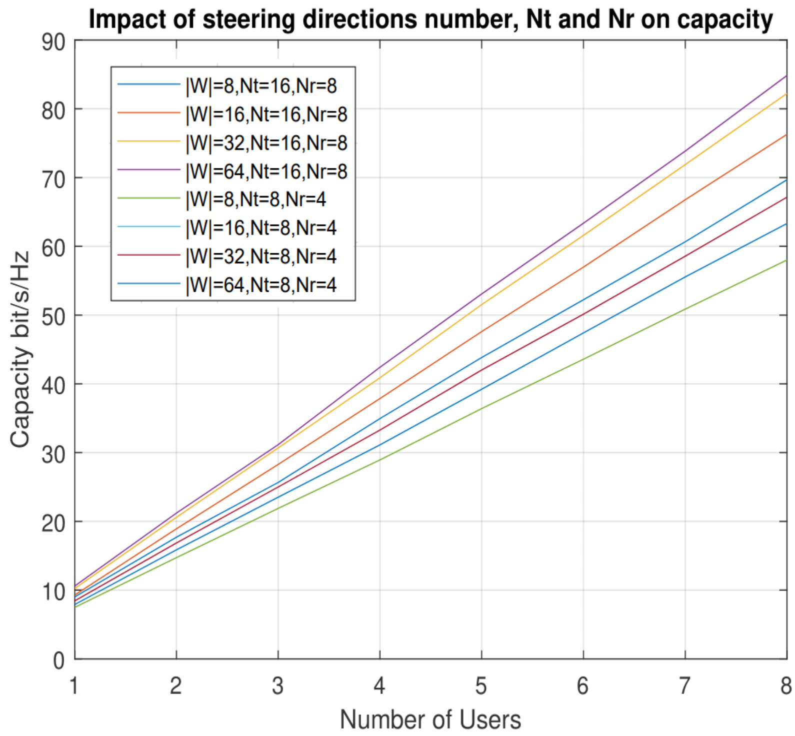

Figure 3.5: Capacity values with different steering directions for given number of antennas

- Secondly, with the existence of one IRS and by comparing LoS and NLoS scenarios, we can claim that system's capacity was increased in the NLoS case, and this is due presence of IRS that provides additional links for some users when the direct path suffers from diffraction, reflection or scattering.

As a result, deployment of IRS has shown some benefits by increasing the total spectral efficiency of a wireless communication system, when direct links experience high path losses.

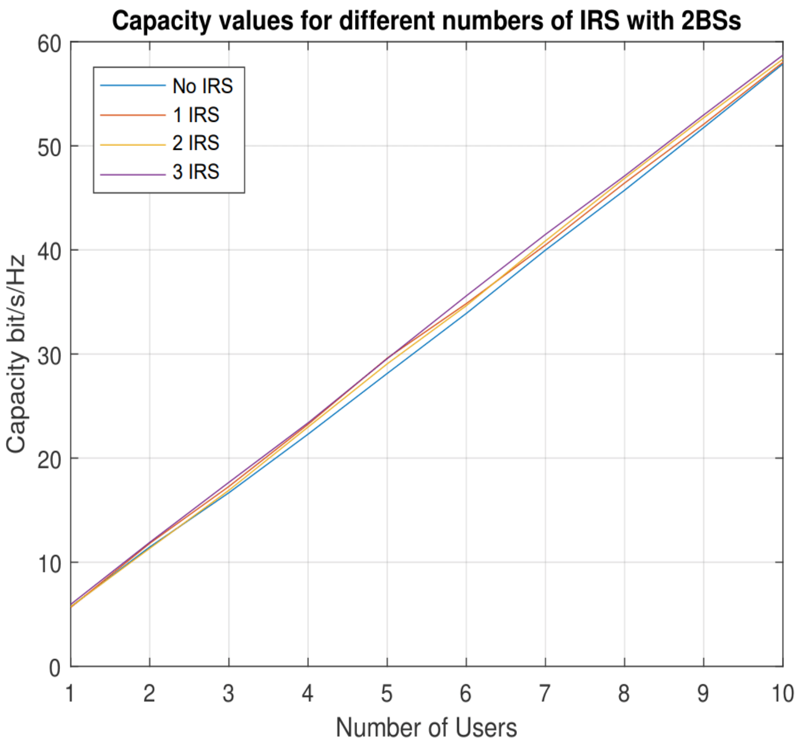

Figure 3.6: Capacity has same values with implementation of IRSs in LoS environment with 2 BSs.

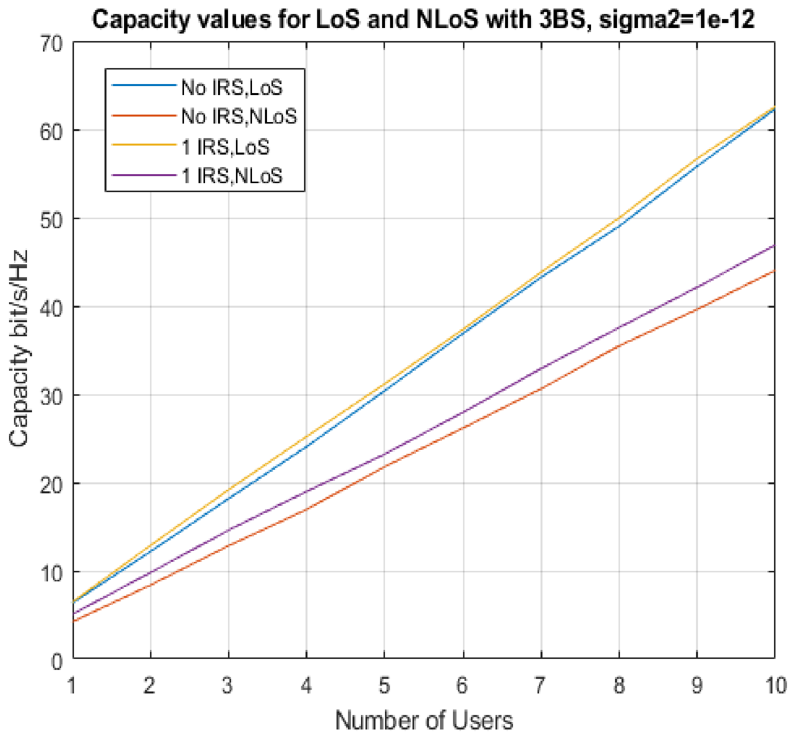

Figure 3.7: Comparison between LoS and NLoS for a single IRS deployment with 3 BSs

Chapter 4

Conclusions

In this work, we investigated the spectral efficiency in the multiple distributed IRSs assisted cell-free MIMO cooperative transmission system. We proposed an efficient solution to maximaze system's capacity by selecting best beamformers at BS, UE and IRS sides, by implementing an exhaustive search and going through all possible codewords. Furthermore, we stress the fact that IRS implementation in cell-free massive MIMO has a crucial impact on system's performance, since it provides additional links in the case where a direct link might suffer from high path loss, diffractions or scattering. Finally, by referring to related works in literature, we can conclude that beamforming, IRSs and cell-free networks are promising technologies to provide high data rates and negligible latencies for future wireless communication.

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